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High-Resolution Reference Evapotranspiration for Arid Egypt: comparative analysis and evaluation of empirical and artificial intelligence models

Abstract

Accurate estimation of evapotranspiration has crucial importance in arid regions like Egypt, which suffers from the scarcity of precipitation and water shortages. This study provides an investigation of the performance of 31 widely used empirical equations and 20 models developed using five artificial intelligence (AI) algorithms to estimate reference evapotranspiration (ET_0) to generate gridded high-resolution daily ET_0 estimates over Egypt. The AI algorithms include support vector machine-radial basis function (SVM-RBF), random forest (RF), group method of data handling neural network (GMDH-NN), multivariate adaptive regression splines (MARS), as well as Dynamic Evolving Neural Fuzzy Interference System (DENFIS). Daily observations records of 41 stations distributed over Egypt were used to calculate ET_0 using FAO56 Penman-Monteith equation as a reference estimate. The multi-parameter Kling-Gupta efficiency (KGE) metric was used as an evaluation metric for its robustness in representing different statistical error/agreement characteristics in a single value. By category, the empirical equations based on radiation performed better in replication FAO56-PM followed by temperature- and mass-transfer-based ones. Ritchie equation was found to be the best overall in Egypt (median KGE 0.75) followed by Caprio (median KGE 0.65), and Penman (median KGE 0.52) equations based on station-wise ranking. On the other hand, the RF model, having maximum and minimum temperatures, wind speed, and relative humidity as predictors, outperformed other AI algorithms. The generated $0.10^\circ \times 0.10^\circ$ daily estimates of ET_0 enabled the detection of a significant increase of 0.12-0.16 mm/decade in the agricultural-dependent Nile Delta using the modified Mann Kendall test and Sen's slope estimator.

Keywords: Potential Evapotranspiration; Machine Learning; MENA; Penman Monteith Equation

1. Introduction

One of the most crucial issues in water management over the past few decades has been the rarity of water availability in some regions of the world and the difficulty of accurately assessing agricultural demand (Shahid 2011). To overcome these issues and improve water use efficiency, an accurate estimation of Evapotranspiration (ET) is required. ET is a combined process of water transfer from the soil-plant system to the atmosphere by evaporation and transpiration. It plays an important role in irrigation management (Adnan et al. 2021), agricultural planning (Ismail et al. 2017; Mehdizadeh et al. 2017), water stress assessment (Mohsenipour et al. 2018; Sanikhani et al. 2019), and climatological change (Roudier et al. 2014; Yu et al. 2020), as it is a key element of Earth's water cycle.

The most accepted method of estimating ET is by measuring reference evapotranspiration (ET_0). ET_0 is the rate of evapotranspiration from a specific crop, mostly grass or alfalfa under certain conditions (Irmak et al. 2003). Its concept is ascended to avoid variability of evaporation parameters among crops and at different growth stages (Gonzalez del Cerro et al. 2021). However, measuring ET_0 in-situ is not only expensive and time-consuming but also subjective to different degrees of uncertainty. Thus, several empirical equations of estimating of ET_0 have been developed. Among them, the Food and Agriculture Organization (FAO) recommended the Penman-Monteith equation (FAO56-PM) as a standard method for reliable estimation of ET_0 (Allen et al. 1998). The performance of the FAO56-PM equation is universally accepted as the most skillful equation in estimating ET_0 . It requires mainly five climatic variables (e.g., temperature, relative humidity, wind speed, solar radiation, and saturated vapor pressure) which limits its use as records of these data are not commonly available especially in data-scarce regions. Thus, several alternative empirical equations are used that require fewer climate records. The performance of the alternative equations depends mainly on climate characteristic patterns which have a significant impact on the estimations (Adnan et al. 2021). Besides, soft computing techniques based on artificial intelligence (AI) algorithms have been widely used to reliably estimate ET_0 from available and recorded meteorological variables (Alizamir et al. 2020). This is driven by the improvement of computer-aided hydrology and water resources models throughout the previous few years (Khosravinia et al., 2020).

In the literature, several studies examined the performance of empirical equations and AI models to select the most robust in estimating ET_0 in different parts of the globe (Gavili et al. 2018; Muhammad et al. 2019). Mehdizadeh et al. (2017) evaluated 16 empirical equations and four AI algorithms (namely gene expression programming (GEP), two different types of Support vector machine (SVM), and multivariate adaptive regression splines (MARS)) in estimating monthly ET_0 in Iran. They found that MARS performed better compared to others. Mattar (2018) tested the performance of GEP models in estimating monthly ET_0 in Egypt and reported the importance of including mean relative humidity (RH) and wind speed at 2 m height (U_2) as predictors in modeling ET_0 in Egypt. Salam et al. (2020) used 13 empirical equations and Random Forest (RF) algorithm to estimate monthly ET_0 in Bangladesh and found that the Abtew (1996) model has the closest estimates and the best linear correlation with FAO56-PM. Recently, Adnan et al. (2021) proved the feasibility of the group method of data handling neural network (GMDH-NN) which used temperatures records as a predictor and found its high performance in Turkey compared to MARS and other empirical equations.

Egypt, as an arid country, is suffering from severe water scarcity. Precipitation can reach 200 mm annually in a narrow strip along the Mediterranean shores. Otherwise, this amount drastically reduces to below 5 mm in inland areas (Hamed et al. 2021c). The Nile supplies Egypt with 98% of its renewable water resource which is mainly consumed in agricultural activities (Hamed 2019). Meanwhile, Egypt is facing external pressure on its perceived Nile water share due to the construction of the Ethiopian Grand Renaissance dam at the far upstream (Sharaky et al. 2019). Furthermore, it faces internal pressure on water due to rapid growth in population and economic status in recent years (Nikiel and Eltahir 2021). This has spurred the country to control and manage its water resources prudently to improve water (re)usage and especially agriculture productivity and food security (AbuZeid 2020; Nikiel and Eltahir 2021).

This study aims to develop a high resolution $0.10^\circ \times 0.10^\circ$ estimate of ET_0 for arid Egypt. In order to gain an accurate estimation of ET_0 , 31 empirical equations and 20 AI models were evaluated against the FAO56-PM estimates at 41 station locations. The multi-parameter Kling-Gupta efficiency (KGE) metric was used as an evaluation metric for its robustness in representing different statistical error/agreement characteristics in a single value. Then, the best method found was chosen to develop the high-resolution ET_0 data for Egypt. Finally, the rate of change in

historical ET_0 was calculated and tested for significance to assess the spatial pattern of trend in ET_0 . This study is among the leading approaches in evaluating several empirical and AI models for ET_0 estimation in Egypt. The findings of this study may facilitate an opportunity for improving crop water estimation and reducing internal pressure on water supply in general.

2. Study area and data sources

2.1. Study area

Egypt covers a land area of nearly 1 million km^2 . Most of the land is flat however the elevation varies from – 139 m in the Qattara Depression in the North to about 2614 m in the elevated mountains in Sinai and 1356 m in the Red Sea Mountains chain, as can be seen in Figure 1. The Nile divides Egypt's land into eastern and western Deserts. These deserts represent most of Egypt's area. Egypt is an arid country. It has mild cold winters, hot summers, and rainfall is rare. The annual rainfall is about 200 mm/year in the northern parts and less than 5 mm/year in the far south (Hamed et al. 2021a; Hamed et al. 2021b; Nashwan et al. 2020; Yassen et al. 2020). Due to the shortage of water, most Egyptian live along the Nile in nearly 4% of Egypt's total land. Agricultural land represents about 3% of the total area of the nation, located along the Nile valley and its delta. Cultivated land in Egypt occupies 85% of the total area of arable land (Omran and Negm 2020).

Figure 1. Topography and meteorological stations' locations in Egypt.

2.2. Data and sources

This study employed two types of data: gauge records and reanalysis gridded data. Daily meteorological observation records at 41-gauge stations distributed all over Egypt's land were collected from the National oceanic and atmospheric administration (NOAA) Global Summary of Days (GSOD) dataset. The records contain observations of maximum, minimum, mean, and dewpoint temperatures ($T_{\max}$, $T_{\min}$, T_{mean} , and T_{dew} , respectively), and wind speed (U_2). The gauges' locations are shown in Figure 1 and descriptive statistics of the records are listed in Table 1.

Table 1. Descriptive statistics of the station records used in the study.

No.	WMO ID	Data range	$T_{\max}$ (°C)	$T_{\min}$ (°C)	T_{dew} (°C)	U_2 (m/s)
1	623250	1994-2021	24.76	17.06	15.18	2.67
2	624050	1943-2021	33.53	16.77	8.76	4.04
3	623930	1957-2021	30.32	15.75	7.26	7.82
4	624350	1957-2021	32.68	16.88	7.93	16.72
5	624550	1999-2021	28.92	17.47	12.08	3.06

No.	WMO ID	Data range	T _{max} (°C)	T _{min} (°C)	T _{dew} (°C)	U ₂ (m/s)
6	624650	1959-2018	28.20	21.24	13.50	7.81
7	624639	1997-2021	30.63	22.07	10.44	4.97
8	624410	1981-1987	28.13	15.28	12.68	7.33
9	624655	2003-2014	26.90	13.16	6.31	4.48
10	623090	1960-2021	25.06	15.99	13.43	3.52
11	623370	1985-2019	26.54	14.53	13.79	2.66
12	624190	2006-2021	33.71	19.19	5.22	3.52
13	624590	1959-2021	28.20	18.30	13.40	6.63
14	624140	1957-2020	34.21	19.56	3.76	7.59
15	623601	2004-2021	25.37	15.68	14.11	4.20
16	624520	2001-2021	27.31	10.64	7.70	3.37
17	624620	1957-1990	28.03	18.92	11.60	10.99
18	623870	1957-2021	30.07	14.82	10.89	11.77
19	623360	1958-1998	26.90	16.16	15.45	4.21
20	623320	1987-2004	24.48	18.58	15.50	6.81
21	623660	1943-2021	27.93	16.51	11.70	3.76
22	623180	1957-2021	25.23	16.22	14.22	5.63
23	624400	1943-2021	27.72	15.35	12.63	3.84
24	623680	1973-1979	26.90	14.81	10.24	3.69
25	623330	1957-2021	24.41	18.83	15.66	8.60
26	624580	2002-2021	27.99	18.12	11.61	3.39
27	623661	2004-2021	29.29	21.93	10.18	5.54
28	624380	1959-1966	28.66	15.29	11.72	5.53
29	623780	1961-1966	27.82	15.30	9.32	4.81
30	624030	2004-2017	33.19	18.42	4.48	2.58
31	623664	2007-2021	24.41	12.11	2.23	2.92
32	624630	1990-2021	30.49	19.96	10.43	7.12
33	623060	1944-2021	24.39	15.51	13.55	8.81
34	623000	1957-1995	25.54	16.77	12.67	8.39
35	623050	1995-2021	24.09	14.03	11.70	4.82
36	623570	1996-2021	27.65	14.89	12.33	2.89
37	624760	2003-2019	31.56	21.59	15.56	3.92
38	624170	1957-2020	29.48	14.97	8.54	4.65
39	624320	1957-2020	31.42	14.46	6.08	4.31
40	624200	1957-2021	30.32	15.06	8.15	7.84
41	624230	1957-2019	30.75	15.09	5.97	11.46

Using reanalysis as a scientific process, an accurate representation of the weather and climate at regular intervals over a longer period can be obtained. European Reanalysis v.5 (ERA5) data is a combination of a numerical prediction model with satellite observation data and other available gauge records. The results of a reanalysis are meteorological fields in a uniform grid with a reasonable temporal resolution over an extended time period that can provide knowledge on

climate conditions (Lompar et al. 2019). ERA5 is the newest edition, which is the fifth overall developed by European Centre for Medium-Range Weather Forecasts (ECMWF). The Integrated Forecasting System (IFS) cycle 41r2 was used to generate ERA5. Gleixner et al. (2020) evaluated ERA5 temperature data compared to observation data. The results show, over Northern and Southern Africa, the correlation is greater than 0.95. Several surface parameters found in ERA5 land were used in this study, such as temperature, dew point temperature, and wind speed from 1981 to 2020. The daily data of ERA5 provided high resolution $0.10^{\circ} \times 0.10^{\circ}$ ($\sim 9 \text{ km}$) grid spacing. Data from ERA5 is accessible from 1981 up to 2–3 months before the current time. Despite the progress that has occurred in model expansion, the potential evaporation field provided in ERA5 is largely underestimated over deserts due to an error in the code, which prevents transpiration when there is no or little vegetation. This limits the use of ERA5 potential evaporation in Egypt and brings the need to develop an accurate high-resolution estimate of ET_0 over Egypt.

3. Methodology

Figure 2 represents a flowchart of the study methodology. Firstly, the FAO56-PM equation was used to calculate ET_0 at different locations for the available observations records. Then, the resulting ET_0 was used as a reference to evaluate the performance of 31 empirical equations and 20 models developed using five AI algorithms. For each AI algorithm, four models were developed. The 1st model employed $T_{\max}$ and $T_{\min}$ as input variables to estimate reference ET_0 . The 2nd model employed $T_{\max}$, $T_{\min}$, and U_2 , whereas the 3rd model employed RH instead of U_2 . Finally, the 4th model employed $T_{\max}$, $T_{\min}$, U_2 , and RH. Random samples represent 70% of the available records of all stations were used to train different models and the remaining 30% were used for testing model performances. The multi-parameter Kling-Gupta efficiency (KGE) metric was used as an evaluation metric for its robustness in representing different statistical error/agreement characteristics in a single value. Afterward, the best performing equation/model was selected and used to estimate ET_0 at ungauged locations over Egypt using ERA5 data at $0.10^{\circ} \times 0.10^{\circ}$ spatial resolution. Finally, the rate of change in annual ET_0 for 1981-2020 was calculated using Sen's slope and significance in change was tested using the modified Mann-Kendal test.

Figure 2. Flowchart of this study's methodology.

3.1. Penman-Monteith equation

The Penman-Monteith equation (FAO56-PM) is an energy balance physical-based equation to estimate ET_o proposed by Allen et al. (1998) and recommended by the food and agriculture organization (FAO). The performance of the FAO56-PM equation is universally accepted as the most skillful equation in estimating ET_o . Due to the limited availability and absence of experimental ET_o in Egypt, the FAO56-PM equation was used as a reference to evaluate the empirical and AI models. However, it requires numerous climatic parameters which are hard to obtain in the data-scarce region as Egypt. The FAO56-PM formula is given in Equation 1:

$$ET_o = \frac{0.408 \times \Delta(R_n - G) + \gamma \frac{900}{(T_{mean} + 273)} \times U_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34U_2)} \quad (1)$$

where ET_o is in mm/day. Δ is the slope of the saturation vapor pressure-temperature curve (KPa/°C). R_n is net radiation (MJ/m²/day). G is the soil heat flux (MJ/m²/day). γ is the Psychrometric constant (KPa/°C). T_{mean} is the mean air temperature at 2 m height (°C). U_2 is the wind speed at 2 m height (m/s). e_s and e_a are the saturation and actual vapor pressure (KPa).

Angstrom-Prescott solar radiation model (Ångström 1924; Prescott 1940) used sunshine duration to determine daily global irradiance for a horizontal surface. Bojanowski et al. (2013) developed satellite-based calibration of the calibration coefficients (i.e. a and b) in Angstrom-Prescott model which has led to high accuracy for estimating solar radiation compared to interpolated ground-based model coefficients. Thus, this study used these site-specific coefficients of the model to obtain more accurate estimation of solar radiation over Egypt leading to better estimation of FAO65-PM ET_o . Furthermore, the sunshine hours (n) were derived using the linear regression proposed Abd el-wahed and Snyder (2015) (expressed in Equation 2) which was developed for reliable estimation of n for arid climate and desert locations.

$$n = 4.352 + 0.232 T_{mean} \quad (2)$$

3.2. Empirical estimation of ET_o

A bundle of 31 empirical equations to estimate ET_o was evaluated in this study. They are categorized based on their bases; namely, temperature-, radiation-, and mass transfer-based equations. They are listed in Table 2 where equations 3-13, 14-23, and 24-33 are temperature-, radiation-, and mass-transfer-based equations, respectively. This bundle of equations is widely and commonly used to estimate ET_o empirically for different climates and regions (Sharafi and Ghaleini 2021).

Table 2. Empirical equations were used in this study. Equations 3-13, 14-23, and 24-33 are temperature-, radiation-, and mass-transfer-based equations, respectively.

Model	Parameter	Equation	
Baier and Robertson (Baier and Robertson 1965)	T_{max}, T_{min}, R_a	$ET_o = 0.109 \times \left(\frac{R_a}{\lambda}\right) + 0.157T_{max} + 0.158(T_{max} - T_{min}) - 5.39$	(3)
FAO Blaney-Criddle (Doorenbos and Pruitt 1977)	T_{mean}	$ET_o = p(0.46T_{mean} + 8.13)$	(4)
Hamon (1963)	T_{mean}	$ET_o = 0.1651L_d RHOSAT \times KPEC$	(5)

Model	Parameter	Equation	
Hargreaves and Samani (1985)	$T_{mean}, T_{min}, T_{max}, R_a$	$ET_o = \left(0.0023 \frac{R_a}{2.45}\right) TD^{0.5} (T_{mean} + 17.8)$	(6)
Ivanov (Romanenko 1961)	T_{mean}, RH	$ET_o = 0.00006(25 + T_{mean})^2(100 - RH)$	(7)
Kharrufa (1985)	T_{mean}	$ET_o = 0.34PT_{mean}^{1.3}$	(8)
Linacre (1977)	T_{mean}	$ET_o = \frac{700(T_{mean} \pm 0.006Z)}{100 - L} + (15 T_{mean} - T_d)$	(9)
Papadakis (1965)	T_{mean}, RH	$ET_o = 2.5(e_{ma} - e_a)$	(10)
Ravazzani et al. (2011)	$T_{mean}, T_{min}, T_{max}, R_a$	$ET_o = (0.817 + 0.00022Z)(0.0023R_a)(TD^{0.5})(T_{mean} + 17.8)$	(11)
Schendel (1967)	T_{mean}, RH	$ET_o = 16 \left(\frac{T_{mean}}{RH}\right)$	(12)
Trajkovic (2007)	$T_{mean}, T_{min}, T_{max}, R_a$	$ET_o = (0.0023R_a)TD^{0.424}(T_{mean} + 17.8)$	(13)
Abtew (1996)	T_{mean}, R_s	$ET_o = 0.53 \left(\frac{R_s}{\lambda}\right)$	(14)
Caprio (1974)	T_{mean}, R_s	$ET_o = \left(\frac{6.1}{10^6}\right) R_s(1.8T_{mean} + 1)$	(15)
Irmak et al. (2003) -Rs	T_{mean}, R_s, RH	$ET_o = 0.489 + 0.289R_n + 0.023T_{mean}$	(16)
Irmak et al. (2003) -Rn	T_{mean}, R_s	$ET_o = -0.611 + 0.149R_s + 0.079T_{mean}$	(17)
Jensen and Haise (1963)	T_{mean}, R_s	$ET_o = \left(\frac{R_s}{\lambda}\right) (0.025T_{mean} + 0.08)$	(18)
Ritchie et al. (Jones 1990)	T_{min}, T_{max}, R_s	$ET_o = \alpha_1(3.87 \times 10^{-3})(R_s(0.6T_{max} + 0.4T_{min} + 29))$	(19)
Makkink (1957)	T_{mean}, R_s	$ET_o = 0.61 \left(\frac{\Delta}{\Delta + \gamma}\right) \frac{R_s}{58.5} - 0.12$	(20)
McGuinness and Bordne (1972)	T_{mean}, R_s	$ET_o = (0.0082T_{mean} - 0.19) \frac{R_s}{1500} (2.54)$	(21)
Priestley and Taylor (1972)	T_{mean}, R_s, RH	$ET_o = \alpha \left(\frac{\Delta}{\Delta + \gamma}\right) \frac{R_n}{\lambda}$	(22)
Turc (1961)	T_{mean}, R_s, RH	$ET_o = 0.013 \left(\frac{T_{mean}}{T_{mean} + 15}\right) (R_s + 50)$	(23)
Albrecht (1950)	T_{mean}, RH, U_2	$ET_o = (0.1005 + 0.297(U_2))(e_s - e_a)$	(24)
Brockamp and Wenner (1963)	T_{mean}, RH, U_2	$ET_o = 0.543(U_2^{0.456})(e_s - e_a)$	(25)

Model	Parameter	Equation	
Dalton (1802)	T_{mean} , RH, U_2	$ET_o = (0.3648 + 0.07223(U_2))(e_s - e_a)$	(26)
Mahringer (1970)	T_{mean} , RH, U_2	$ET_o = (0.15072) \sqrt{3.6U_2} (e_s - e_a)$	(27)
Meyer (1926)	T_{mean} , RH, U_2	$ET_o = (0.375 + 0.05026(U_2))(e_s - e_a)$	(28)
Penman (1948)	T_{mean} , RH, U_2	$ET_o = \left(2.625 + \frac{0.000479}{U_2}\right)(e_s - e_a)$	(29)
Rohwer (1931)	T_{mean} , RH, U_2	$ET_o = (3.3 + 0.891(U_2))(e_s - e_a)$	(30)
Szasz (1973)	T_{mean} , RH, U_2	$ET_o = 0.00536(T_{mean} + 21)^2 (1 + RH)^{2/3} \mathcal{F}(U_2)$	(31)
Trabert (1896)	T_{mean} , RH, U_2	$ET_o = (0.3075)\sqrt{U_2} (e_s - e_a)$	(32)
WMO (Gangopadhyaya 1966)	T_{mean} , RH, U_2	$ET_o = (0.1298 + 0.0934(U_2))(e_s - e_a)$	(33)

189

190 ET_o is the reference evapotranspiration in mm/day except for McGuinness and Bordne, and
191 Ritchie equations, ET_o in cm/day. R_n is net radiation (MJ/m²/day). T_{max} , T_{min} , T_{mean} and T_d are
192 the maximum, minimum, mean, and dewpoint daily air temperature in °C respectively, except
193 T_{mean} in McGuinness and Bordne equation wherein °F. G is the soil heat flux (MJ/m²/day). γ is
194 the Psychometric constant (KPa/°C). U_2 is the mean daily wind speed at 2 m height. Z is the
195 elevation in m. L is the local latitude in degree. R_a is extraterrestrial radiation (MJ/m²/day). TD is
196 the difference between the T_{max} and T_{min} in °C. R_s is solar radiation in MJ/m²/day except in Ritchie,
197 Makkink, Turc, and McGuinness and Bordne equations, R_s wherein Cal/m². e_s and e_a are the
198 saturation and actual vapor pressure (hPa), except for Rohwer, Papadakis and penman are in KPa.
199 e_{ma} is the saturation vapor pressure at monthly mean daily maximum temperature (KPa). λ is the
200 latent heat of evaporation (MJ/Kg). Δ is the slope of the saturation vapor pressure-temperature
201 curve (KPa/°C). RH is the average relative humidity percentage. p is a constant having two values
202 depending on the number of the month (0.27 and 0.28). L_d is the daytime length in multiples of 12
203 h. $\mathcal{F}(U_2)$ is a function of wind speed. RHOSAT is the saturated vapor density (g/m³). ESAT is the
204 saturated vapor pressure (mbar). KPEC is a calibration coefficient (1.2) and α is a constant (1.26).
205 At Ritchie equation, α_1 is a coefficient that depends on T_{max} and calculated as follows:

$$\text{if } 5^\circ\text{C} < T_{max} \leq 35^\circ\text{C}, \alpha_1 = 1.1 \quad (34)$$

$$\text{if } T_{max} > 35 \text{ }^{\circ}\text{C}, \alpha_1 = 1.1 + 0.05(T_{max} - 35) \quad (35)$$

$$\text{if } T_{max} < 5 \text{ }^{\circ}\text{C}, \alpha_1 = 0.01 \times \exp [0.18(T_{max} + 20)] \quad (36)$$

206

207 **3.3. AI models**

208 **3.3.1. Support vector machine**

209 SVM is a machine learning technique that can be used for both classification and regression.
 210 SVM's core concept, which is extrapolated to support vector regression (SVR), is to separate two
 211 or more classes linearly with a hyperplane, by selecting support vector points. SVR is a powerful
 212 forecasting tool for resolving regression issues using the kernel function. ET_o prediction using this
 213 technique is obtained using the following formulation.

$$\hat{y}_t = b_o + \sum_{i=1}^N (\alpha_1 - \alpha_i^*) K(\chi_k, \chi) \quad (37)$$

214 where $\hat{y}_t$ is the target predict variable, b_o is bias, α_1, α_i^* are the dual variables, and $K(\chi_k, \chi)$ is the
 215 kernel function. The radial basis function kernel (RBF) was used in this study.

216

217 **3.3.2. Random Forest**

218 RF, which is extensively used in different research fields, is an ensemble tree-based method in
 219 which trees are trained in a random subset and can be used with bagging or pasting, bagging is
 220 more frequent and commonly used. When the number of trees grows, it also brings more
 221 randomness and achieves the concept of generalization. Rather than looking for the best
 222 characteristic to split a node, it looks for the best feature among a set of random sub-nodes.
 223 Randomly various features (m_{try}) selected in each split node, and the number of regression trees
 224 (n_{tree}) are the parameters used by RF. Prediction obtained by the model after training is
 225 represented as:

$$\hat{y}_t = \frac{1}{M} \sum_{m=1}^M T_m(f_t) \quad (38)$$

226 where M is the number of regression trees, T_m denotes a single decision tree, and f_t is a vector of
 227 predictors.

Root mean square error was used to select the optimal model. Two-fold cross-validation was used to calibrate m_{try} and the final value used was 3. The number of regression trees used in this study was $n_{tree} = 500$.

3.3.3. Group method of data handling neural network (GMDH-NN)

GMDH-NN is a nonlinear machine learning model with a statistical analysis approach, used for classification and regression problems by identifying the complex relationship between input and output of the system. The GMDH-NN model has the ability to handle several inputs variables and predict a single output, using different layers in the model. Each layer output considers an input to the next layer (Adnan et al. 2021). The GMDH-NN's layer structure can be presented as:

$$\hat{y}_t = a_o + \sum_{i=1}^M a_i x_i + \sum_{j=1}^M \sum_{i=1}^M a_i a_j x_i x_j + \sum_{k=1}^M \sum_{j=1}^M \sum_{i=1}^M a_i a_j a_k x_i x_j x_k + \dots \quad (39)$$

where x_i = i^{th} input variable; M = total number of input variables; and a_i = weight associated with x_i . To minimize the difference between the observed values and the output values generated by GMDH-NN, the weights are optimized using the least-squares method.

3.3.4. Multivariate adaptive regression splines (MARS)

MARS is a non-parametric flexible regression model, used to predict persistent numerical target variables. In this algorithm, input variables are separated into intervals, and each interval is fitted with a basis function. The information about independent variables is represented by the basis function. The initial and final points of a basis function are known as knots, and they are defined in a specific range. The MARS model is divided into two stages: In the first stage (forward step), the model uses a constant value to estimate the value of the target variable. This variable is the mean of the data for the target variable. An over-fitted and complex model with a huge number of knots is constructed at this stage. In the second stage (backward step), checking all basis functions added in the first stage is carried out. Finally, the model was obtained (Mehdizadeh et al. 2017).

3.3.5. Dynamic Evolving Neural Fuzzy Interference System (DENFIS)

DENFIS is an AI learning algorithm based on an Adaptive Neural Fuzzy Inference Systems (ANFIS) introduced by Kasabov and Qun (2002). DENFIS uses an evolving clustering algorithm that takes into account the greatest possible distance between the points and the center of the cluster. Thus, it can handle the noise in the data (Ye et al. 2022). Furthermore, DENFIS learning approach assesses the position of the input vectors in the feature scape is assessed by fuzzy neural networks and then a dynamic process forms a fuzzy inference system to predict the output based on the nearest fuzzy rules. In comparison to other well-known models, DENFIS showed to be able to learn complex temporal sequences in an adaptable manner (Ye et al. 2022).

3.4. Evaluation metric

The performances of the empirical equations and the AI models were statistically assessed using the robust KGE metric. The KGE integrates several statistics into one metric and gives an overall score of the skill of each method in estimating the ET_o compared to FAO56-PM estimations. As shown in Equation 40, it incorporates three components of observed and simulated data: Pearson's linear correlation (r), coefficient of variability (α), and bias ratio (β).

$$KGE = 1 - \sqrt{(r - 1)^2 + (\alpha - 1)^2 + (\beta - 1)^2}$$
$$\alpha = \frac{\sigma_{sim}}{\sigma_{obs}} \quad (40)$$
$$\beta = \frac{\mu_{sim}}{\mu_{obs}}$$

where, σ_{sim} is the simulation standard deviation, σ_{obs} is the FAO56-PM standard deviation, μ_{sim} is the mean of simulation, and μ_{obs} is the mean of FAO56-PM estimations. In case there is a perfect match between the pairs of ET_o time series, the KGE values shall be one. Otherwise, the KGE values shall be lower than 1 to $-\infty$. A positive KGE value indicates a “good” overall skill, whereas a negative KGE value indicates a “weak” model skill (Knoben et al. 2019).

3.5. Trend Analysis

3.5.1 Sen's slope estimator

Sen's slope method (Sen 1968), is a non-parametric statistical method for fitting a line for the mean of the slope. Sen's slope estimator (1968) turned out to be an effective tool for constructing linear relationships. Estimating slopes between series data points as follows:

$$Q_i = \frac{\chi_j - \chi_k}{j - k} \quad \text{for } i = 1: N \quad (41)$$

where Q_i is the median slope between data points, χ_i and χ_j is measured respectively at j and k (where $j > k$). Sen's slope estimator clearly shows the trend over the entire period.

3.5.2 Modified Mann Kendall test

Unlike the standard Mann-Kendall test (Kendall 1948; Mann 1945), the modified Mann-Kendall test, proposed by Hamed and Rao (1998), detect the unidirectional trends in time series with the existence of autocorrelations. The main advantage of the modified Mann-Kendall is that it eliminates the influence of long-term persistence in time series on trend significance. Several studies revealed the robustness of the modified Mann-Kendall rather than the standard version in testing the significance of change in climatic time series (Nashwan and Shahid 2019a; Nashwan et al. 2019; Sa'adi et al. 2017). The 95% confidence level was adopted in this study. Further information regarding the modified Mann-Kendall test can be found in literature, for example in the following references (Iqbal et al. 2019; Sa'adi et al. 2017; Salman et al. 2019; Shahid and Khairulmaini 2009; Sharafati et al. 2019).

4. Results

4.1. Evaluation of empirical equations

Heat-scatter plots between ET_o observed from FAO56-PM against each simulated ET_o from the empirical equation are shown in Figure 3. As observed in Figure 3, most temperature, radiation, and mass transfer tend to overestimate the simulated ET_o except Baier and Robertson, and Penman. Radiation-based equations generally have a smaller overestimation than temperature-based equations. The mass-transfer-based equations tend to overestimate $ET_o > \text{than } 6 \text{ mm/day}$ expect for Penman equation. On the other hand, the FAO Blaney-Criddle, Abtew, Makkink, McGuinness

305 and Bordne, Priestley and Taylor, and Turc equations underestimated values of $ET_o > 6$ mm/day.
306 Overall, temperature, radiation-based equations perform better than mass transfer-based equations,
307 except for the Penman equation which performs better than the other mass-transfer-based
308 equations. Besides, Ritchie equation simulation of ET_o was better aligned with the diagonal line
309 1:1.
310

Figure 3. Heat scatter plots of different ET_0 empirical equations estimates against FAO56-PM (n= 430688).

4.2. Performance evaluation

Figure 4 presents box-and-whiskers plots of KGE scores for the 31 ET_o empirical equations. Plots (a-c) present the components of the KGE, the r , α , and β , aiming at presenting which component effect the final KGE score that is presented in plot (d). The red vertical lines present the optimal value of the scores which is unity. By category, the empirical equations based on mass transfer performed poorly in replicating FAO56-PM estimates compared to the temperature- and radiation-based equations. The mass-transfer-based equations achieved KGE scores far from unity. Among them, the Penman equation was found the best having a median KGE of 0.52, and Albrecht was found the worst among all equations (median KGE equals -19.04). The performances of the temperature- and radiation-based equations were comparable. Among the temperature-based equations, Hargreaves-Samani had the highest skill with a median KGE of 0.73. However, Ritchie, radiation-based equation, had better performance than Hargreaves-Samani and was the best among the radiation-based equations having median r , α , β , and KGE 0.90, 0.80, 1.14, and 0.75, respectively. On the other hand, the mean median scores of the KGE components r , α , and β expressed as $|r - 1|$, $|\alpha - 1|$, and $|\beta - 1|$, are 0.21, 0.80, and 0.46, respectively. The mean median score of KGE of all equations is -0.80 and without considering the mass-transfer-based equations results are 0.51. The empirical equations thus performed remarkably worse in terms of α meaning that bias in estimates is the issue rather than correlation and ratio in co-efficient of variation. In turn, the α value was the dominant component in the final KGE scores due to the squaring of the three components of KGE (refer to Equation 40).

Figure 4. Box-and-whiskers plots of (a) linear correlation (r), (b) coefficient of variability (α), (c) bias ratio (β), and (d) Kling-Gupta efficiency (KGE) used for evaluating the 31 empirical equations compared to observed ET_o obtained from FAO56-PM. The optimum value is represented by the vertical red line.

KGE scores were ranked at each gauge station location to identify the best empirical equation per location. Out of the 31 equations used, eight equations dominated the top station-wise ranks. Namely, they are Ritchie, Penman, Caprio, Irmak (Rn), Ivanov, Hargreaves Samani, McGuinness, Jensen, Kharrufa, Priestley, and Papadakis, and their spatial distribution is presented in Figure 5. The Ritchie equation was found the best at eight locations, followed by Penman, Caprio, and Irmak (Rn) each at five locations, then Ivanov and Hargreaves-Samani each at four locations, McGuinness, and Jensen each at three locations, Kharrufa at two locations and finally Priestley, and Papadakis each at one location. Furthermore, the figure also shows the distribution of the type of each best equation per location. It can be seen that there is a spatial pattern in equation type over Egypt. The radiation-based equation dominated the majority of Egypt (25 out of 41 locations: 61%). The temperature-based equations dominated the northern west edge of the country where solar radiation is the lowest, and the mass transfer-based equations dominated the western desert. At a few locations in the middle and east regions of Egypt, temperature-based equations

were found to be the best whereas the radiation-based equations were the best in the nearby locations. However, it was found that the 2nd best equation for most of these locations was a radiation-based equation. For example, station no 27 on the Red Sea coast had Papadakis (KGE 0.86) as the best equation followed closely by the radiation-based Caprio equation (KGE 0.85). The same was observed for station no. 21 at Cairo where Ritchie was the 2nd best. Furthermore, station no 31 in Saint Catherine Mount where Caprio equation had a close skill to Kharrufa equation.

Figure 5. Spatial distribution of the best performing empirical equation at each station location.

4.3. Evaluation of AI models

Figure 6 presents box-and-whiskers plots to show the distribution of the available records from the 41 meteorological stations for the four climatic variables (i.e., T_{max} , T_{min} , U_2 , and RH). Furthermore, the figure presents the distributions of 70% of the available records which were chosen randomly and used in the training stage, as well as the remaining 30% which were used in the testing stage of the 20 AI models. The training set contains 70 % (301824 daily data) of

collected records and the remaining 30% (128864 daily data) of the data. It is clear that the three data groups of each climate variable had nearly the same distribution, which is crucial for data-driven models that are highly affected by the distribution of the training and testing samples.

Figure 6. Data ranges for all records from 41 stations, and for data used in training and testing stages for (a) maximum temperature (°C), (b) minimum temperature (°C), (c) wind speed (m/s), and (d) relative humidity (%).

In this study, 20 models were developed using five AI algorithms having four different combinations of the model's inputs to estimate the FAO56-PM ET_o . Figure 7 illustrates the FAO56-PM ET_o and simulated ET_o from AI models, each row represents the same algorithm with the four different combinations of the model inputs. Combinations were utilized to estimate the daily ET_o using the SVM, RF, GMDH-NN, MARS, and DENFIS. Twenty models were implemented to evaluate the performance of various climate data combinations. The first combination used two climatic data T_{max} and T_{min} . The second and third combinations were generated by the addition of U_2 and RH into the first combination, respectively. U_2 and RH were added to the first combination to create a new fourth combination. The scatter plot in Figure 7 clearly shows that overall better performance of the 4th combination compared to others. The ET_o simulated by RF4 was considerably aligned with the diagonal line 1:1 and closely followed by the

estimates of SVM4. Table 3 shows a comparison between models compared to FAO56-PM in respect to KGE for the training and testing stages. Remarkably, the testing KGEs were $\geq$ than those of training stage indicating a good generalization of models' performances. Furthermore, the RF models presented the best results across the four combinations of input parameters. It was also found that the U_2 data when combined with $T_{\max}$ and $T_{\min}$ as input parameters led to improvement in estimating ET_0 compared to using only $T_{\max}$ and $T_{\min}$. Furthermore, the improvement in the 2nd combination is better than in the 3rd which used RH except in MARS and DENFIS. DENFIS in the 1st combination (DENFIS1) recorded testing KGE 0.83 which was equal to the RF1. SVM had better testing KGEs following RF in the 2nd, 3rd, and 4th combinations which were 0.93, 0.87, and 0.98, respectively. DENFIS4 showed weak results compared to other corresponding models.

Figure 7. Heat scatter plots of 20 AI models output ET_0 estimation against FAO56-PM ($n=128864$).

Table 3. KGE values across the training and testing phase for each AI model.

Model	Model input combination	Training KGE	Testing KGE
Support vector machine			
SVM 1	$T_{\max}, T_{\min}$	0.78	0.78
SVM 2	$T_{\max}, T_{\min}, U_2$	0.93	0.93
SVM 3	$T_{\max}, T_{\min}, RH$	0.86	0.87
SVM 4	$T_{\max}, T_{\min}, U_2, RH$	0.96	0.98
Random Forest			
RF 1	$T_{\max}, T_{\min}$	0.81	0.83
RF 2	$T_{\max}, T_{\min}, U_2$	0.92	0.94
RF 3	$T_{\max}, T_{\min}, RH$	0.87	0.92
RF 4	$T_{\max}, T_{\min}, U_2, RH$	0.97	0.99
Group method of data handling-Neural Network			
GMDH 1	$T_{\max}, T_{\min}$	0.79	0.80
GMDH 2	$T_{\max}, T_{\min}, U_2$	0.90	0.91
GMDH 3	$T_{\max}, T_{\min}, RH$	0.87	0.87
GMDH 4	$T_{\max}, T_{\min}, U_2, RH$	0.95	0.95
Multivariate adaptive regression splines			
MARS 1	$T_{\max}, T_{\min}$	0.80	0.80
MARS 2	$T_{\max}, T_{\min}, U_2$	0.82	0.83
MARS 3	$T_{\max}, T_{\min}, RH$	0.87	0.87
MARS 4	$T_{\max}, T_{\min}, U_2, RH$	0.96	0.96
Dynamic evolving neural fuzzy interference system			
DENFIS 1	$T_{\max}, T_{\min}$	0.80	0.83
DENFIS 2	$T_{\max}, T_{\min}, U_2$	0.78	0.85
DENFIS 3	$T_{\max}, T_{\min}, RH$	0.81	0.86
DENFIS 4	$T_{\max}, T_{\min}, U_2, RH$	0.77	0.88

4.4. Estimating ET_0 in ungauged locations

As presented in previous results the RF4 had the top performance compared to others besides its KGEs were even higher than those of empirical equations. Thus, the RF4 was adopted to estimate ET_0 in ungauged location in Egypt. The four input parameters required for RF4 were obtained from ERA5 to estimate daily ET_0 all over Egypt at $0.10^\circ \times 0.10^\circ$ horizontal resolution. Figure 8 shows the mean daily ET_0 spatial distribution for the period 1981-2020. The ET_0 ranges from 2.30 to 6.72 mm/day, which increases spatially by going southeast from the north of Egypt, except the Red Sea mountains chain. ET_0 rates in central Egypt range from 4.30 to 4.92 mm/day.

Figure 8. Mean daily ET_0 calculated over a period 1981-2020.

The daily ET_0 values for each grid point were cumulated and averaged during the years from 1981 to 2020 to derive the annual averages. Time-series data were then utilized to estimate rate of change and determine the significance of the shifts in the data. The color ramps in Figure 9 describe the rate of change obtained by Sen's slope estimator for ET_0 (Figure 9 e), as well as the four predictors (Figure 9 a-d), to examine the driving factors. A dot in the middle of each grid point indicates the significance of change as obtained using a modified MK test for a 95 % level of confidence.

The Sen's slope estimator test revealed an increase in the annual average T_{max} and T_{min} across all of Egypt's rates from 0.26 to 0.53 and 0.20 to 0.60 °C/decade, respectively. The largest change in T_{max} occurred in the north and east of the Nile Delta. However, for T_{min} , it occurred in the far south of Egypt. The modified MK test showed a significant decrease in RH in the northeast of Egypt. The changes in RH were detected in the range of -1.13 to -0.05 %/decade. The highest rate of decrease -1.13 %/decade was observed East of the Nile Delta and north of Sinai. The U_2 trend shows varieties of increases and decreases. However, the changes were only significant mainly along the Red Sea shores and south of Sinai. As can be observed in Figure 9 (e), the changes in ET_0 were found to be significantly increasing all over Egypt, with the highest change of 0.16-0.18 mm/decade observed in the far southeast of Egypt.

Figure 9. Spatial distributions of the rate of change in (a) T_{max} , (b) T_{min} , (c) U_2 , (d) RH, and (e) ET_o as estimated using the RF4 model. Color ramps indicate the rate of change obtained using Sens's slope estimator. The significant changes ($p > 0.05$) are marked with a dot.

5. Discussion

Most of the previous studies had adopted several statistical metrics for the evaluation of either empirical equations or AI models in estimating the FAO56-PM ET_o . The use of several metrics can generally produce a reliable assessment of modeling techniques rather than the use of a single metric. However, the use of several metrics may provide contradictory results due to the fact each metric reflects the state of specific statistical characteristics (e.g., error, association, etc.) (Hamed et al. 2022; Nashwan and Shahid 2019b). This study used only the KGE which is a composite metric that integrates estimates of bias, correlation, and variability, to gain the advantages of using multiple metrics while avoiding related complexities in using multiples.

Based on median KGE values, the radiation-based Ritchie empirical equation was found the best (median KGE 0.75) to replicate the FAO56-PM estimates of daily ET_o . It was followed by the temperature-based Hargreaves-Samani and the radiation-based Priestley et al. (median KGE 0.73 and 0.71, respectively). Ritchie was found the best based on station-wise ranking followed by Penman, Caprio, and Irmak (-Rn). Also, the results proved the better performance of the RF models in general compared to other AI algorithms. Thus, this study recommends Ritchie equation as a substitute method for the FAO56-PM when required observations are limited.

The present study revealed that Ritchie equation, which is a radiation-based method, had a superior performance in modeling ET_o in the arid climate of Egypt. Furthermore, the study results illustrated the overall better performance of radiation-based equations than temperature- and mass-transfer-based equations. These findings agree with previous studies' results. Del Cerro et al. (2021) evaluated the performance of various radiation- and temperature-based empirical equations in the semi-arid region of south India and found that Ritchie had performed the best. Furthermore, they concluded that radiation-based equations are best suited to estimate ET_o in the study region. Also, Tabari et al. (2013) and Sharafi and Ghaleni (2021) concluded that the radiation-based models were the best-suited equations, while mass transfer-based equations had the worst performances in Iran. Tabari et al. (2012) found the Ritchie equation gives an acceptable performance in modeling crop ET Tabriz, Iran. Farzanpour et al. (2018) proved that a calibrated version of Ritchie equation was among the best in semi-arid regions in Iran. Tikhamarine et al. (2020) also confirmed that Ritchie equation had a reliable estimate of ET_o in Algeria. On the contrary, Ritchie equation was found to be the worst at estimating ET_o in other climate types, rather than arid, as in Muhammad et al. (2019) and Feng et al. (2016).

The finding of the present study revealed an overall good performance of AI models compared to empirical equations in simulating daily mean ET_o in arid Egypt. Besides, this study found that the models having U_2 and RH as input parameters with T_{max} and T_{min} were better in performance. This agrees with the finding of Mattar (2018) in Egypt. Furthermore, this study found that including U_2 gave better performance than including RH along with T_{max} and T_{min} .

Among AI models, the RF models were the most accurate, closely followed by SVM. These findings can be confirmed by previous studies. Wen et al. (2015), Mehdizadeh et al. (2017), and Adnan et al. (2021) confirm that, overall, the soft computing approach performs better than empirical equations, which is in agreement with the present study finding. Furthermore, Mehdizadeh et al. (2017) reported the strong ability of SVM- polynomial in estimating monthly ET_o in Iran. Furthermore, GMDH-NN had acceptable performance, as found by Adnan et al. (2021) in Turkey. Also, this study found that DINFIS models were the worst among the applied algorithms, as was similarly reported by Muhammad Adnan et al. (2020) when modeling monthly ET_o in China.

The main advantage of using RF models is their flexibility, meaning that when the dimensions of the characteristic parameters increase, the RF method does not generate overfitting, but better results are still achieved. The RF algorithm outperforms SVM when tested with identical characteristic parameters (Jia et al. 2013). Han et al. (2018) conducted a comparative analysis to evaluate the behavior of RF and showed that RF has outstanding properties in terms of classification accuracy, stability, and robustness to characteristics, as demonstrated by the comparison. In particular, they discovered that RF is significantly better when the training samples are constrained in a number of analytical studies. These may be the reasons why the RF models outperformed other algorithms.

The high-resolution estimation of daily ET_o and trend analysis showed that locations of relatively low ET_o (north of Egypt) are experiencing a higher increase. Meanwhile, locations of high ET_o (south and east of Egypt) are experiencing an equal and lower rate of increase. This indicates that ET_o shall be overall higher in future climate states. This may have severe consequences for agriculture and water resources in Egypt in the future. The high rate of evaporation has already had a significant impact on Lake Nasser (Egypt's national reserve of fresh water) and thus the Egyptian water budget (Salih et al. 2019).

6. Conclusions

Accurate estimation of ET_o using the standard FAO56-PM is challenging when required climate data isn't available as in most regions around the globe. In this study, the abilities of five AI algorithms (i.e., SVM, RF, MARS, GMDH-NN, and DENFIS) and 31 empirical equations in modeling daily ET_o compared to the FAO56-PM equation were evaluated. First, at 41 locations covering Egypt, the KGE evaluation results showed that Ritchie had the best overall performance (median KGE 0.75) and found the best at the highest number of stations based on a station-wise ranking compared to others. In contrast to the several meteorological variables required for the FAO56-PM computation of ET_o , the Ritchie equation just requires T_{max} , T_{min} , and R_s . The result illustrates that Ritchie equation can be used as a substitute for FAO56-PM when data is scarce. Secondly, different combinations of T_{max} , T_{min} , U_2 , and RH were used as inputs to train AI models to target the FAO56-PM ET_o . The RF model was generally the most accurate in predicting daily mean ET_o , closely followed by SVM, whereas DENFIS provided the worst prediction at the third and fourth combinations of input variables. Thus, this study recommends using the RF model in predicting ET_o . According to the findings of this study, the RF1 model, which requires only maximum and minimum temperature, can be employed for worst-case scenarios. Using the RF model, irrigation schedulers can get an accurate estimate of ET_o in Egypt, without the need for the full set of climatic data. Thirdly, the RF4 model was used to generate a 0.1-degree resolution of ET_o , all over Egypt, using ERA5 data. Finally, Sen's slope estimator and modified Mann-Kendall test showed a significant change in ET_o in most locations in Egypt over the past 40 years.

Considering the lack of reliable observation records for the required inputs of the FAO56-PM in most developing countries, the present study shall be useful for determining ET_o in arid climates, such as Egypt, using simpler and more accurate methods. Furthermore, this study enables peers to produce better estimations of drought and aridity status in Egypt, which employs common methods such as standard precipitation evaporation index and aridity index. Thus, it can provide enhanced strategies for the adaptation and mitigation of such events. Locally, irrigation schedulers can get an accurate estimate of ET_o , without the need for the full set of climatic data.

The developed high resolution ($0.10^\circ \times 0.10^\circ$) daily estimation of ET_o is freely available online (DOI:10.6084/m9.figshare.18551084) in Comma-Separated Values (CSV) format. The daily records cover the land of Egypt and temporally span from 1981 to 2020.

Future works may investigate the future change in ET_0 regionally in Egypt, using the state-of-art Coupled Model Intercomparison Project phase 6 (CMIP6) models with the use of RF models of this study. Also, the high-resolution data can be used in downscaling and bias-correction of CMIP6 model estimations. Furthermore, peers can provide a locally calibrated version of the Ritchie equation in Egypt.

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Competing Interests

The authors have no relevant financial or non-financial interests to disclose.

Author Contributions

All authors contributed to the study's conception and design. Material preparation, data collection methodology, and analysis were performed by Mohamed Tarek Sobh and Mohamed Salem Nashwan. The first draft of the manuscript was written by Mohamed Tarek Sobh and Mohamed Salem Nashwan and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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